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## TOWARD AN ASPIRATION-LEVEL THEORY OF OPEN INNOVATION

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## TOWARD AN ASPIRATION-LEVEL THEORY OF OPEN INNOVATION

### ABSTRACT

Although open innovation has become increasingly established in the management literature, comprehensive theoretical explanations of what drives firms to be open are sparse. Taking the perspective of the behavioral theory of the firm, we conceive of open innovation as a form of non-local search, arguing that firms will turn to open innovation when substantially under- or overperforming relative to their aspirations. We further enquire how this relationship is moderated by firm-specific innovation-related resources: human capital, R&D investment, and patents. Employing a representative survey of UK firms, we find some evidence of moderation, allowing us to present explanations of search through open innovation and contribute to the behavioral theory of the firm itself.

**Keywords:** open innovation, behavioral theory of the firm, aspiration levels, performance feedback, non-local search, SMEs

**JEL Codes:** L21, O31, O32, M11, M13

## INTRODUCTION

Few concepts on the management of innovation have recently gathered similar levels of attention as has open innovation—from practitioners and researchers alike (Dahlander & Gann 2010; West et al. 2014). Defined as “the use of purposive inflows and outflows of knowledge to accelerate internal innovation, and expand the markets for external use of innovation, respectively” (Chesbrough 2006b, 1), open innovation promises to bring about substantial increases in the efficacy and efficiency of R&D, and enable firms to create innovation ecosystems and dominant designs. At the same time, open innovation implies substantial organizational change, and is thus subject to significant inertial forces (Chiaroni et al. 2010). Governance structures and individual-level routines need to be overhauled to full make use of this approach to innovative activity (Alexy et al. 2013b; Foss et al. 2011; Lakemond et al. 2016). Thus, while open innovation potentially offers considerable benefits, to achieve those, firms need willing to bear significant costs in terms of managerial time and effort.

The question that follows for research and managerial practice is thus: when and why would companies be willing to bear these costs? While many laudable contributions have begun tackling this question, we note an absence of theoretically-motivated work that puts strategic managerial action at the center of attention. One stream in this literature looks at drivers of one-off engagement in open innovation, such as the search for solutions to specific internal problems (Jeppesen & Lakhani 2010) or the trading of individual technologies on external markets (Arora et al. 2001). Another stream explores external triggers that may cause managers to rethink their relative evaluation of closed and open innovation, such as economic crises (Di Minin et al. 2010), industry-level demand shifts (Henkel et al. 2014), appropriability (Laursen & Salter 2014), or competition between strategic groups (Polidoro & Toh 2011). In contrast, intra-firm

drivers explaining why firms would engage (more) in open innovation are largely summed up as managers being able to identify a business case (Henkel 2006). However, such approaches fall short of coherently theorizing general patterns in open innovation activity that are derived from company-specific attributes, such as their performance-levels or resource endowment.

In this paper, we intend to address this shortcoming by looking at engagement in open innovation through the theoretical lens of the behavioral theory of the firm (Cyert & March 1963; hereafter: BTF). According to the BTF, firms (or rather: their boundedly-rational managers) set aspiration levels—performance thresholds the firm should meet. If performance is within acceptable limits, firms do business-as-usual. If aspirations are not met, managers initiate costly (problem-based) non-local search processes to remedy the situation (see Greve 2003). When overfulfillment of aspirations provides the firm with abundant resources, managers may use these to invest into (slack-based) non-local search to sustain its overperformance (see Argote & Greve 2007). In this view, open innovation becomes a form of non-local search (Alexy et al. 2013a; Laursen & Salter 2006), as firms need to change how they search for technological solutions or market applications, using a variety of practices. In turn, we posit that under- or overachieving set aspiration-levels will drive firm engagement in open innovation.

We further expect this relationship to be moderated by firms' innovation-related resources (see also Audia & Greve 2006), specifically human capital, R&D investments, and patents. These three factors should not only represent the critical innovation-related resources that managers may draw upon in open innovation processes; they should also influence how managers perceive the relationship between firms' aspiration-performance and engagement in open innovation. Regarding human capital, at high values it may *generally* alter the cost of open innovation search. Building on Afuah and Tucci's work (2012) on crowdsourcing as local

search, we propose that high human capital may enable companies to establish stable conduits to their environment through which they can access external sources even at “normal” levels of firm performance. Concerning past investments, we expect that underperforming firms with a large R&D base should be particularly prone to regard underperformance as threatening, and will thus look for help outside their boundaries even more strongly. We further expect that managers apply similar thinking with regards to existing outputs of R&D, such as patents.

To test our model, we take a practice-based view on open innovation. We rely on a survey instrument specifically designed to study the open innovation practices of small and medium-sized companies by the UK Innovation Research Center in 2010 (Cosh & Zhang 2011; Mina et al. 2013; 2014; Theyel & Cosh 2012). This survey allows us to use richer information compared to previous empirical studies based on Community-Innovation-Survey-type databases, as it collects information on engagements in practices that can be associated with the notion of open innovation. Combining survey data with firm-level financial information, we evaluate the relationship between firms’ aspiration levels, resource endowment, and their engagement in open innovation practices.

We only see some of our hypotheses supported by our analyses. While we do not find a direct effect of aspiration levels, we see how the relationship between aspiration-performance and open innovation search is moderated by human capital, in that this factor ‘flips’ the respective relationship. For R&D investments, we also find a turning of the U-shape: firms with high levels of R&D investment search more than low-R&D firms, and this difference becomes more pronounced in particular with increasing levels underperformance. Finally, for patenting activity, we gain surprisingly little traction.

Supported by a series of robustness checks, we contribute to the innovation and

organization literatures in three ways. First, we present an initial attempt of an aspiration-level theory of open innovation: a coherent conceptual framework that helps explain drivers of open innovation engagement. By showing how aspiration-levels and firm-idiosyncratic attributes come together to help explain firm engagement in open innovation, we extend the literature on the sources of openness (e.g., Di Minin et al. 2010; Henkel et al. 2014). Second, our findings point toward a potential extension of the BTF itself (Cyert & March 1963), by shedding light on the actual search activity conducted. Extending earlier insights by Afuah and Tucci (2012), we show how firm-internal factors lead to varying levels of perceived costs of collaboration, which in turn extends the scope of local search. Finally, the practice-based view of open innovation we develop may help improve measurement quality and enhance compatibility between research results in this increasingly important area of study.

## **THEORY AND HYPOTHESES**

### **Linking the Behavioral Theory of the Firm and Open Innovation**

The behavioral theory of the firm is fundamentally an explanation of how firms search, and how these decisions to search are based on firms' aspiration levels, which are rooted in their social and historical performance (Argote & Greve 2007; Cyert & March 1963; Gavetti et al. 2012; Greve 2003). The key insight from this theoretical framework is that organizations performing at expected or normal aspiration levels are not likely to engage in search or will hold constant their search efforts: given that searching beyond what is currently known is costly, firms would rather search locally, i.e., within their own boundaries and known fields of knowledge. However, when faced with significant over- and underperformance, managers may become increasingly willing to bear the cost of non-local search:<sup>1</sup> underperformance may lead managers to undertake 'problem-based' search, as they seek to respond to impending pressures.

Overperformance may lead firms to engage in ‘slack-based’ search, in which firms engage in purposeful experimentation in an attempt to sustain their overperformance, with the excess resources available to them helping to cushion the cost of searching.

Although this approach has long been a central tenant of managerial theory, it was given renewed impetus by the major growth of research about how under- and overperformance shaped different aspects of managerial decision-making. In particular, research on the Japanese shipbuilding industry demonstrated that the BTF offered a strong predictor of R&D spending (Audia & Greve 2006; Greve 2003; 2007; 2008). This finding was also seen in other sets of industries, suggesting that search—using R&D spending as proxy—was tied to levels of aspiration-performance (Chen 2008; Chen & Miller 2007). Over time, scholars have also used the BTF to explore other aspects of firm behavior, highlighting the importance of aspirations in shaping network ties in banking (Baum et al. 2005), investments in railroads safety (Baum & Dahlin 2007), acquisitions (Iyer & Miller 2008), corporate illegality (Mishina et al. 2010), and entrepreneurial activity (Wennberg & Holmquist 2008), and university knowledge sourcing (Bruneel et al. 2016).

In this paper, we return to one of the key elements in the BTF—the link between aspiration levels and actual search *behavior*. While search behavior is a central tenet in the BTF—and related theories (Nelson & Winter 1982)—reviews of the BTF make clear how most theorizing related to the BTF is about the search process on a fairly abstract level (see Argote & Greve 2007; Gavetti et al. 2012; Shinkle 2012): for example, literature in the N-K tradition, while talking explicitly about local and non-local search, rarely looks at how firms are *actually* searching—whether it is through internal investments, collaboration, networks, expenditures on R&D, acquisitions, etc. Similarly, other literature links aspiration-levels to changes in behavior,



and postulates the changes to originate from search processes, but without any actual search activities being directly examined. While notable exceptions exist (e.g., Gavetti & Rivkin 2007; MacAulay et al. 2014; Maggitti et al. 2013), by and large, the practices and processes that firms use for problem-based and slack-based search remain underexplored.

Accordingly, we focus on firms' use of open innovation as a lens to better understand how search is manifested as an organization's adoption of a set of managerial practices to harness external pathways to knowledge creation and exploitation. Open innovation has been often been described as a non-local search activity (e.g., Afuah & Tucci 2012; Alexy et al. 2013a; Laursen & Salter 2006). It is non-local both because open innovation implies searching in a different location as well as in a different fashion. Location here may be geographical, but also relate to innovation efforts that will include knowledge domains previously unfamiliar to the firm. As regards the style of search, open innovation allows for knowledge to flow across the boundary of the firm—both inward and outward, with or without monetary incentives or intellectual property protection (Dahlander & Gann 2010), and regarding both the identification of technological solutions as well as new needs for existing ideas (Alexy et al. 2013a; von Hippel 1988). Open innovation is thus clearly different from local search—or 'innovation as usual'—and engaging in it means overcoming substantial inertia and cost. Foss and colleagues (2011) show how the benefits of open innovation are conditional upon re-designing an appropriate organization. These redesigns include both managerial-strategic considerations as well as day-to-day job routines of R&D workers (Alexy et al. 2013b; Henkel et al. 2014).

### **Predicting Firm Engagement in Open Innovation Practices**

Our attempt is to explain the degree (or breadth, see Laursen & Salter 2006) of a firm's activity in open innovation (also, e.g., Lee et al. 2010; Love et al. 2011). To do so, we take a

practice-based view: we conceive of open innovation as a set of different, often complementary practices firms will apply to solve innovation-related problems. Once managers have decided to engage in non-local search through open innovation, a wide variety of practices exist on which they may draw, such as innovation intermediaries (Jeppesen & Lakhani 2010), crowdsourcing (Afuah & Tucci 2012), or even patent auctions (Fischer & Leidinger 2014).

Following such a practice-based approach, our baseline hypothesis rests on a core tenet of the BTF: bringing together the BTF with the open innovation literature, we suggest that under- and overperformance relative to aspirations will increase firms' willingness to bear the cost of non-local search through open innovation, and thus to use more open innovation practices.

Fundamentally, firms performing below aspirations are under pressure to identify pathways to return to higher relative performance (Greve 2003). Open innovation provides a means for underperforming innovation-active firms to gain access to new resources that augment their own, both in the creation as well as the commercialization of innovative ideas (Chesbrough 2003). Underperforming firms may become increasingly desperate in seeking these external resources, as only they may provide a key to return to their aspiration level. In contrast, firms performing near their aspiration levels should have little incentive to engage with external actors.

In the case of overperformance, firms are liable to have a surfeit of resources, which will enable them to allow individuals and teams to engage in 'slack search' (Argote & Greve 2007). Such activities break away from organizational accountability and may even be considered 'foolish' (e.g., March 2006). Overperforming organizations have slack resources using which staff may undertake playful projects: activities not directly subject to organizational monitoring, measurement, or selection. Here, open innovation practices are especially germane to enable slack search, given they provide opportunities for organizational members to tap into new areas

through collaboration with external actors. External actors' knowledge domains and practices are liable to differ considerably from the focus organization, and therefore they are attractive for partners in generating greater combinatorial novelty (e.g., Fleming 2001).

Combining these two perspectives, we thus posit as our baseline hypotheses:

*H1a. Under-performing firms will exhibit higher levels of open innovation activities.*

*H1b. Over-performing firms will exhibit higher levels of open innovation activities.*

### **The Effect of Firm Resources on Open Innovation Activity**

Although the previous discussion locates the use of open innovation practices in the context of firm aspirations, it says little about how firm resources may shape the choice to use open innovation practices in light of firm performance relative to aspirations. We propose that firms may perceive the cost of searching non-locally through open innovation (as per their aspiration-performance) differently conditional upon their resource endowment. We focus our efforts on three key innovation-related resources: a firm's human capital, its R&D investment, and its patenting activity. These resources include the key inputs and outputs of R&D for many industries, and each has been found to be important in explaining why firms engage in open innovation or do so more efficiently and effectively (e.g., Alexy et al. 2013b; Fosfuri et al. 2008; Foss et al. 2011). Extending work by Audia and Greve (2006), who show how underperforming firms that are endowed with less resources show lower levels of risk-taking, we argue that resource endowments may also shift how firms perceive under- or overperformance and approach the search for non-local solutions. Accordingly, we enquire whether and to what degree the availability of these key innovation-related resources moderates the effect of firms' performance relative to aspirations on their engagement in non-local search through open innovation. Below, we take each of our three potential moderators—human capital, R&D

investment, and patents—in turn.

### ***The role of human capital***

It is clear that human capital—the skills and talents of its employees—plays a primary role in shaping a firm’s ability to search externally. Without skilled staff, firms would lack the prior knowledge to successfully utilize external knowledge (Cohen & Levinthal 1990). High human capital also makes firms a more attractive partner for external actors, and firms can also draw upon their skilled employees’ extensive social capital to reach out to external actors (Coleman 1988). Indeed, prior research has shown that the level of firms’ human capital is positively associated with a variety of measures of open innovation (Escribano et al. 2009).

We argue that human capital may also mitigate the effect of aspiration-performance on open innovation. Fundamentally, human capital represents a (semi)permanent conduit to engage external sources (e.g., Podolny 2001). As such, the existing networks individuals with high human capital bring to the firm may continuously be used to lower the costs of absorbing knowledge from external sources (Rosenberg 1990). With such networks in place, non-local search on these networks is *always* (relatively) less costly to the organization, so it should not need problems or slack to overcome associated perceived hurdles. Similarly, human capital represents an endowment for using external knowledge that is available for use irrespective of the firm’s current performance. Like a radio frequency, it is an organizational capability that is always turned on, and therefore performance relative to aspirations may be less salient in motivating search choices in its presence. Finally, firms with high levels of human capital are liable to have a strong repertoire of external contacts and relationships they can draw on also in times of crisis, and therefore should perceive less of a need to broaden their scope of open innovation practices as aspirations levels fall below or rise above expected levels.

To summarize, we maintain that high-human-capital firms will be more likely to engage in non-local search. Thus, in case of under- or overperformance, no particular relative increase in search activity should be expected. We thus expect that, at high levels of human capital, the (approximately) inverted u-shaped relationship between performance and open innovation would flatten, indicating that open innovation would be tied less strongly to past performance.

*H2. At higher levels of human capital, the strength of the relationship between under/overperformance and the level of open innovation activity will decrease.*

### ***The effect of R&D investments***

The importance of investment in R&D for open innovation and external search has long been acknowledged in the literature (Chesbrough 2003). R&D creates new knowledge that firms can exploit themselves or in collaboration with others. By investing in internal R&D, firms are not only generating new products, processes and services, but also building their capability to better exploit external knowledge (Cohen & Levinthal 1990). Internal R&D may also spur open innovation when firms need to find solutions to problems, in particular when these are perceived to be distant from their current body of knowledge (Afuah & Tucci 2012; Jeppesen & Lakhani 2010). In addition, R&D expenditures provide a potential opportunity to develop technologies that can be traded in markets for technology (Arora et al. 2001). Finally, R&D makes a firm a more attractive partner for externals, as it is signal of the quality of the firm that it may possess useful resources that external actors may acquire or exchange (Laursen & Salter 2014).

The role of R&D for open innovation in the context performance relative to aspirations is less well understood. We argue that past R&D efforts combined with aspiration-performance will change the urgency with which firms consider search efforts through open innovation. To illustrate our point, we stylistically distinguish four extreme cases: whether firms are under- or overperforming, and whether they are low or high in R&D investment.

Open innovation should be most attractive to underperforming, yet R&D-intensive firms, as these have both means (R&D outputs) to engage in open innovation as well as motive (past failure) to bear the costs of non-local search. Their investments in R&D will make them more attractive partners to externals and their underperformance motivated to find and accept help; they should thus be more willing and (predictably) more successful in finding external partners within with to work with on open innovation efforts. Oppositely, underperforming firms that spend little on R&D should fail to see how they could recoup the costs of non-local search, and thus decide against this option: not only do they lack the necessary internal resources to engage in open innovation, they are also unattractive partners given they are poor track record and have little to offer and leverage in any open innovation relationship.

In the case of overperformance, we would expect the moderating effect of R&D to be less extreme. In general, higher-performing organizations may be prone to success bias (Powell et al. 2011) and thus less likely to overhaul completely the way in which they innovate. Also, while past research provides arguments for why different levels of available firm resources should influence the effect of underperformance on search behavior and risk-taking (Audia & Greve 2006), no clear causal arguments seem to exist for the presence of such a moderating effect for overperformance. In short, we would expect high-performing firms to use the excess research to engage in open innovation as slack-based experimentation, but it is not clear why their level of past R&D investment should moderate this relationship. Taken together, we thus only expect a significant difference in how R&D investment moderates the effect of underperformance on firms' open innovation engagement. With increasing levels of performance, the difference in effects should disappear. We hypothesize:

*H3. At higher levels of past R&D investment, underperforming firms will be engaging more in open innovation. The difference in engagement in open innovation between firms*

*low and high in R&D investment will disappear with increasing levels of performance.*

### ***The effect of patenting activity***

In order to engage in open innovation, firms often need to ensure they have formal intellectual property (e.g., Chesbrough 2006a; Zobel et al. 2016). IP, such as patents, has sometimes been described as the currency of open innovation, because its possession allows firms to engage in markets for technology (Arora et al. 2001)— a trading chip required to be allowed to participate in such processes (Hall & Ziedonis 2001). As Laursen and Salter (2014) suggest, formal IP also allows firms to more successfully collaborate with other firms, which may require formal IP to be in place before engaging into collaboration. In particular, large firms tend to prefer partners with patents given they seek to ensure downstream value capture of these collaborations and clarity about the ownership of inventions (Alexy et al. 2012). In addition, the possession of IP is a (weak) signal of firm quality, suggesting that the firm has valuable inventions that have been upheld by an external body (the patent office) (Baum & Silverman 2004). However, the complementarities between IP and external collaboration may be subject to diminishing returns, as a very strong focus on formal IP may deter firms from engaging in open innovation due to fears on involuntary external spillovers (Laursen & Salter 2014).

Building on the notion of complementarities between IP and external collaboration, we suggest that the possession of patents may moderate the effect of past performance on open innovation. The logic here is akin to the preceding hypotheses (with the difference that patents are usually an output of R&D in the search of a market, and past R&D may rather require other firms' R&D assistance in further technological development): underperforming firms with patents still have assets to trade on a market for technologies, and, in doing so, return to higher level of performance. Oppositely, underperforming firms with little or no patents should see little

or no scope to engage in open innovation in a way that the costs of non-local search may be recouped. This is because although underperformance may force them to seek external assistance, these organizations will have little to trade in the market for technology, lacking the signal of quality and potential appropriation that patents provide. Finally, for the case of overperformance, we would again expect the effect of patents on the relationship of past aspiration-performance on open innovation to be of decreasing importance.

*H4. At higher levels of past patenting, underperforming firms will be engaging more in open innovation. The difference in engagement in open innovation between firms low and high in patenting will disappear with increasing levels of performance.*

## **DATA AND METHODS**

### **Empirical Context and Survey Design**

Open innovation pertains to a wide variety of sectors in manufacturing and in services (Chesbrough 2011; Chesbrough 2003). It should be particularly prominent when value creation is complex and thus split amongst actors in the value chain, who specialize in order to master technological difficulties or decrease the cost necessary to keep up with technological progress. Also, open innovation should happen in small and large firms alike (van de Vrande et al. 2009): while large firms have more resources to offer in open innovation relationships and to manage them subsequently, small firms, due to their liabilities of smallness, will more often need to search beyond their boundaries for solutions to their innovation-related problems.

As such, we chose to rely on a survey instrument that systematically sampled small and medium-sized (SMEs) technology and service firms in the UK and followed a practice-based approach to open innovation: the data we use in this paper are drawn from the UK~IRC Open Innovation Survey (Cosh & Zhang 2011), purposefully designed and launched in 2010 to study the open innovation practices of SMEs (see also Mina et al. 2013; 2014; Theyel & Cosh 2012).



This survey used systematic random sampling to draw a sample of 12,000 UK firms with between 5 and 999 employees from Bureau van Dijk's FAME Database, which also contains detailed financial company-level information on UK and Irish businesses. After carrying out pilot tests in different size groups and sectors, five waves of questionnaires were sent out by post between June and November 2010.<sup>2</sup> 1,202 firms (10%) completed the survey. FAME data was used to check for non-response bias, and no significant difference between respondents and non-respondents in terms of size, turnover, and year of firm formation was found (Cosh & Zhang 2011).<sup>3</sup>

### **Sample**

In this study, we can draw on a sample size of 313 firms, due to number of reasons. First of all, 245 firms who completed a shorter version of the survey had to be excluded. Another 45 firms were deleted due to incomplete responses. Finally, 593 firms had been removed in the process of matching the survey data with the latest wave of the FAME dataset. That is, these firms were too young to have the track record that is needed to create measures for aspiration-levels. Finally, we removed 6 more firms that were actually larger than the original sampling criteria—these were UK subsidiaries of larger multinationals. Regarding the composition of our data, we see some differences compared to the UK~IRC sample: our firms are on average larger, with higher R&D expenditures and a higher share of human capital, but no difference in patenting. Compared to the UK~IRC dataset, firms with 100-500 employees are over-represented. Finally, we also see some differences in the structure of our dependent variable. We will attend to the latter issue by using weights on observations, and discuss the general issue below, together with the other robustness checks we conducted.

By relying on two main sources of data, our study helps reduce issues of common method

bias (Podsakoff et al. 2003). It also enables us to lag some of the independent variables to capture them for the time *before* the survey. Specifically, we generate the dependent variable from survey questions that pertain to the years 2008 to 2010. In turn, the independent variables are mostly taken from publicly available sources, such as the FAME database. However, as the financial records for some SMEs were incomplete,<sup>4</sup> to help compute a growth rate for those firms with missing reports for 2008, we use information for 2009 or 2010. In addition, we draw on information from our survey to help calculate the firm's recent sales growth, as the survey asked firms to report their change in sales over the previous three years. Accordingly, the final sample blends data from FAME and with sales information from the survey. We performed a Wilcoxon test that confirmed that it was possible to combine the two data sources. In addition, the survey question refers to an objective and concrete measure and therefore it is unlikely to subject to significant reporting bias. It is also retrospective by nature.

## **Variables**

### ***Dependent variables.***

The dependent variable in our study is *open innovation breadth (OI Breadth)*, captured by the number of different open innovation practices in which firms may engage (see Appendix). Firms were asked to indicate the use of these activities without the word open innovation mentioned once throughout the entire survey. Drawing on this measure, we hope to overcome a shortcoming in the open innovation literature, which has presented varying definitions and operationalizations of open innovation, often hard to separate from related constructs such firms' attempts to absorb external knowledge, its collaboration strategy and out-licensing of technology, or co-patenting. We argue that such approaches must remain incomplete, as they fail to capture the wider set of managerial practices associated with open innovation, which, if truly

strategic, must include a broader range of efforts. Also, our approach should reduce confusion and expectancy bias regarding the term open innovation itself (Podsakoff et al. 2003).

Following previous literature (Laursen & Salter 2006; Leiponen & Helfat 2010), we compute the scope or “breadth” of open innovation activities by adding up these 15 activities. The focal summative open innovation index has a high degree of internal consistency with a Cronbach’s alpha of 0.86. Around 20% of our sample does not practice any open innovation activities; 2% are engaged in all 15 activities. This suggests that open innovation practices are subject to a high degree of variation among firms and that few firms attempt to put in place the full range of practices. Given that the decision to engage in open innovation may be the result of a preceding selection decision, we will also conduct a respective robustness check. We also explored further the unidimensionality assumption embedded in our use of an index of open innovation.<sup>5</sup> Both (polychoric) exploratory and confirmatory factor analyses suggested a three-factor model (see Appendix). Of these, two factors capture R&D-related partnerships: one contains more traditional tools (like contract research) and another those practices typically associated with the term open innovation (like open source). We will draw on those as alternative dependent variables in our robustness checks.

Finally, we also observe significant variance in the specific practices chosen by firms, with some (costlier) practices selected very few times over all. To be able to see whether these cost considerations were in line with our theorizing, we calculated a *weighted index of OI practices*, in which the selection of a practice used rarely by the rest of the sample scored more highly than the choice of a commonly used one (see Bozeman & Gaughan 2007).

### ***Independent variables.***

The first of our independent variable relates to aspiration levels. Following Greve (2007),

we constructed measures of *under- and overperformance* as a combination of a social (SAP) and a historical aspiration level (HAP). To operationalize SAP and HAP, we extensively reviewed the literature for appropriate measures. Specifically, we needed to overcome the problem that, for a large share of our sample (consisting mainly of small and young firms, with many in services), return on assets, while probably the most widely used measurement in the literature, was neither an appropriate measure, nor reliably available. Following Cyert and March (1963), Greve (2008), and Bromiley and Harris (2014), we decided on sales growth as our measure of performance: industry-wide sales figures are not only available to researchers, but to practicing managers as well. Also, sales growth should be an ambition shared by most, if not all our sample firms. In turn, we derived SAP as the firm's past performance relative to the average of other firms' performance seen as competitors, using the 4-digit SIC level data from the Office of National Statistics. HAP is a weighted average of the past historical aspiration levels (over the past five years) and the past performance of the same firm. The respective formulas are:

$$SAP_{i,t} = \Sigma G_{i,t} / N - 1$$

$$HAP_{i,t} = \alpha_2 HAP_{i,t-1} + (1 - \alpha_2) P_{i,t-1}$$

Here, G is the industry sales growth (excluding firm i), P firm sales growth, and t and i time and firm subscripts. For SAP, we draw on the year-to-year growth figures at the beginning of the time frame captured by the survey (i.e., 2006-2008); for HAP, we use a five-year window starting with the 2003-2004 figures—we successfully validated these results when using a three-year-window to increase our number of observations. As described above, we would also modify these time windows if we lost what would seem to be a valid observation otherwise.

Next, following Greve (2003),  $\alpha_2$  was estimated to 0.5 using a grid search and taking the combination with the highest model likelihood.<sup>6</sup> The final aspiration level is constructed as:

$$A_{it} = \alpha_1 SAP_{i,t} + (1 - \alpha_1) HAP_{i,t}$$

The weight  $\alpha_1$  was again estimated by a grid search and yielded 0.81.

We measured *human capital* by the share of employees with a higher education degree. Given we are interested in R&D resources, we chose to operationalize *R&D investments* (logged) using R&D expenditures, rather than intensity. For *patenting activity*, we employed several operationalizations: whether the firm patented or not (dummy), the firms' patent stock (count), and a quality-controlled measure that also incorporates the citations their patents have received. Of course, our interest does not lie in the direct effect of these variables, but in their interaction with those capturing aspiration-performance. In constructing these, we mean-centered the human capital and R&D investments variables to ease interpretation of the coefficients.

### ***Controls.***

We further include measures for *firm size* (log of employee count) and *age* (time since founding). Larger firms may be expected to have greater resources to engage in open innovation than smaller firms. Young firms may lack time to build external relationships, and therefore are less likely to engage in open innovation. *Absorbed slack* is measured as the ratio of selling, general, and administrative expenses to sales (George 2005). We also control for *sectoral technological intensity* by introducing dummy variables for high-tech, medium-tech manufacturing and traditional business services and knowledge intensive business services, the reference category being low-tech manufacturing.

### **Modeling and Estimation Strategy and Sources of Bias**

We test our hypothesis using zero-inflated negative binomial (ZINB) estimations, due to over-dispersion of the dependent variable OI Breadth and the large share of firms with no open innovation activities. The Vuong test suggests that we should prefer the use of ZINB against

other count data models,<sup>7</sup> which we keep as robustness checks. In addition to the control variables, we introduce in the inflated model perceived competitive pressure, measured by the number of competitors, a sales revenue growth objective, and an industry-level formal IP protection measure. The first two of these measures are taken from the survey, and are self-reported. The measure of industry IP is an aggregate of the use of formal protection mechanisms across the survey responses by industry. In order to account for unobservable heterogeneity, we clustered standard errors by 2-digit industry codes.

The use of different data sources such as FAME alongside the original survey helps to limit threats of common method bias in our estimations (Podsakoff et al. 2003). In addition, many of our measures are clear and objective activities, such as sales growth or R&D spending. Furthermore, in the survey design, we tried to account for all recommended design elements to reduce bias, such as using different anchors/scales, neutral tone and separating key variables into different parts of the survey. Finally, we also applied standard tests, such as Harman's one factor test, and found no indication for common method bias.

In addition, we performed all useful standard tests of multicollinearity, on unstandardized data. We found high correlations and changes in coefficients between estimation models only to be caused by the interaction terms—as was to be expected. Given that even the introduction of interaction terms into our models has negligible effects on the t-statistics of other, unrelated variables, we conclude that our findings should not substantially suffer from multicollinearity.

## RESULTS

*--- Insert Table 1 about here ---*

Before turning to our multivariate analysis, we first take a look at the descriptive statistics of our variables of interest, reported in Table 1. We find that all our variables of interest show

sufficient variance, and, for our resource variables, that a large enough share of observations occurs around the extreme values of their range. However, we also find that only about 1% of the aspiration-level-values lie outside the interval ranging from  $\pm 0.7$  (so we will limit our simulations to this reduced range), and only 6% outside the  $\pm 0.35$  interval, suggesting that we need to be cautious when interpreting extreme values of our interactions.

Table 2 contains the results of the ZINB regressions. Model 1 contains the baseline terms. In Model 2, we add the aspiration-level main effects for under- and overperformance. Models 3, 4, and 5 separately introduce the interaction terms with human capital, R&D investment, and patenting activity. We use these models to look at improvement of model fit from the interaction terms, which is significant for all moderating variables. Finally, Model 6 contains the full model—it is the basis of our hypotheses tests and underlies the simulation results (Zelner 2009) shown in Figures 1 to 3.<sup>8</sup>

*--- Insert Table 2 and Figures 1 to 3 about here ---*

Given the complexity of our hypotheses, any interpretation of the coefficients in Table 2 requires caution. Looking across all models, we see that our baseline effects (Model 2) and moderators (Models 3-5) seem to gain some empirical traction. However, concerning H1, Model 2 suggests that it should not be accepted given we do not find significant effects in the expected directions.

As to the deeper meaning of this, we look at the moderation effects in Model 6 and the corresponding simulation results. Figure 1 indicates how for low levels of human capital, we find the search patterns predicted by the behavioral theory of the firm with a u-shaped relationship between aspiration-performance and search. Interestingly, these patterns do not only disappear for high-human-capital firms: rather, we find the relationship turns around completely, in that

high-human capital firms search significantly more at average levels of performance—the difference at the extremes of under- and overperformance is not significant, but this changes for many of the robustness checks. H2, however, can only be partially accepted.

Looking at Figure 2, we see that it is firms with high levels of R&D investment whose search patterns most closely resemble what would be expected by the BTF. We also find that, when underperforming, these firms are more likely to engage in open innovation search in the present, as predicted by H3. The difference decreases with aspiration-performance reaching the ‘normal level’ (i.e., zero); however, different from what is predicted H3, increases again for increasing overperformance. H3, too, can thus only be partially accepted.

For H4, we find results opposite to what we predicted: rather than resembling the results for R&D investment (H3), the joint effects of patenting activity and aspiration levels resemble those for human capital (H2). However, the marginal effect of aspiration-performance is insignificant, and remains so for other operationalizations of patenting. Accordingly, we cannot reject the null hypothesis for H4.

Given we found two of our four predicted relationships to be outright rejected and the other two only partially validated, we began experimenting with using separate measures for HAP and SAP. In a series of additional regressions we conducted (available on request), we first discovered that most of the effects we observe are driven by SAP: not only does it already carry more weight in the joint aspiration-performance measure, but in additional regressions where we replace the joint aspiration-performance measures with their respective HAP and SAP components and the corresponding interactions, we find *precisely* those shapes predicted by H2 and H3 (with even the difference on the right turning insignificant, as predicted by H3) for the SAP-based interactions (no effects for H4), and no true moderating effects for HAP. This would



suggest that, overall, it is performance considerations vs. the industry rather than comparisons to the firm's past that drive managers to consider open innovation more strongly conditional upon their firm's human capital and R&D investments. While the literature is still unclear about which type of aspiration dominates the other, some previous studies have pointed to the prevailing role of social aspirations (Mishina et al. 2010).

### **Robustness Checks**

To corroborate our findings, we ran a series of robustness checks. First, we conducted several additional estimation methods, including negative binomial regression and OLS. In addition, we explicitly tried to account for firms' decision to engage in open innovation by modeling it as a two-step process. We first predicted firms' decision to engage in open innovation activity at all (using the same variables as for zero inflation) and included the resulting inverse Mill's ratio in a second step: a zero-truncated negative binomial model (tnbreg in Stata), also checked against a simple Heckman OLS specification. Across all specifications, our results remained qualitatively identical.

Second, we engaged in several checks of our dependent variable. We began by applying weights to our regression to account for the differences in the distribution of the dependent variable when comparing our sample and all 1,202 original survey responses. Moreover, as mentioned above, we subjected our dependent variable to factor analysis. Our results remained qualitatively unchanged (and, in parts, even improved, in particular regarding the effect of human capital) when using either of the R&D-partnership-related measures as dependent variable. However, we gain almost no traction for the non-R&D partnerships.

Next, we used the "weighted index" version of the dependent variable described earlier—as stated before, while the first method described in this paragraph puts weights on a full

observation, this approach puts a score on a specific type of open innovation search, the value of which is higher the less often the practice is chosen by all sample firms.

Similarly, we also split the dependent variable according to whether a search practice may be regarded as formal-contractual or informal. Then, we reran all estimation method described in the results and in this section if applicable (the index is of course not a count variable), using the three alternative specifications of the DV. Again, results remained qualitatively unchanged—to our surprise, there were not even any major differences between formal and informal practices (cf. Grimpe & Sofka 2009; van de Vrande et al. 2009).

Finally, we replaced our dependent variable with another summative scale measuring on how many of our practices firms reported to have increased their engagement over the survey period. The patterns we found are also qualitatively identical to those reported in the paper.

## **DISCUSSION AND CONCLUSION**

Our study set out to establish a link between the behavioral theory of the firm and open innovation: conceptualizing engagement in open innovation as non-local search, we argued, but could not directly find, such activity to be triggered by firms under- or overperforming aspiration levels. Taking a closer look at this relationship, we predicted and found that a direct effect was hidden by moderating factors, most notably human capital and past R&D investment, which substantially affected the relationship between aspiration-performance and engagement in open innovation, with only low-human-capital and high-R&D-investment firms exhibiting search behavior in line with the patterns corresponding to what the BTF would have predicted. We further saw our results improve when focusing our attention on social aspirations.

### **Theoretical Implications**

Building on our findings, we make three contributions to literatures on innovation and

organization. First, we extend recent attempts at clarifying the emergence of open innovation, which have largely focused on factors external to the firm and the strategic group it is embedded in so far (e.g., Di Minin et al. 2010; Henkel et al. 2014). Given we observe firms in the same industry choosing different stances toward openness (Alexy & Reitzig 2013), we argued that perspectives that account for firm idiosyncrasies need to be increasingly considered. To do so, we conceptualize open innovation as a search for solutions (to both market-related and technology-related problems) beyond the boundary of the firm, engagement in which is motivated through past over- or underperformance and moderated by firm-level resource endowments. These, we posit, will influence how costly firms will perceive non-local search through openness. We show that high-human capital firms use more open innovation at average performance, as do low-performing firms that have high level of R&D investments. The latter is also in line with earlier work showing how SMEs often use open innovation out of necessity, rather than opportunity (van de Vrande et al. 2009), as well as general notions of non-local problemistic search (Audia & Greve 2006; Greve 2003). In addition, we also find indications of slack-based search for firms high in R&D investment. Finally, we highlight that it is largely performance comparisons to rivals that drive how firms view engagement with external actors.

At the same time, the fact that patents have no effect on the aspiration-performance relationship with open innovation (see Figure 3) is intriguing. Our analyses (Model 5) suggest that the effect has some traction on its own, but weakens when controlling for the moderating effect of the other resources, a dynamic that is usually observed in mediation analysis. However, given that patents usually are the outcome of investments in human capital or R&D, we would argue a mediation effect in the other direction would have seemed more likely. Given the limitations of our empirical set-up, we can only speculate about reasons for this result. One

potential explanation is that, for many of the industries we observe, earlier-stage R&D resources captured by human capital or R&D investments lend themselves to more and possibly more valuable open innovation activities than exchanging singular patents, and encourage future research into these effects. However, to draw any strong inferences about this question, richer longitudinal data will be required. Finally, future qualitative work that studies the process of defining aspirations should also look into why our main effect of aspiration-performance gains little traction: are we using a suboptimal measure of aspiration (see also Bromiley & Harris 2014; Shinkle 2012), or could our results be attributed to the dominance of small firms in our sample (see Audia & Greve 2006) or other aspects of the sample composition (see endnote 4)?

Our second contribution lies in extending our insights to the BTF more broadly. Here, our study may help improve our understanding of actual search behavior, given we directly measure different forms of firms' search activity (e.g., Maggitti et al. 2013) rather than the search process as a whole or its outcomes (see, e.g., Argote & Greve 2007; Gavetti et al. 2012). In doing so, we show how search behavior can be explained by the BTF as long as firm idiosyncrasies are taken into account. In particular, we highlight that high-human capital firms search more non-locally at normal performance levels. We argue that for such firms, open innovation is no different from local search, because high levels of human capital represent a permanent conduit through which external knowledge can be continuously accessed. More generally, this finding suggests that processes or techniques exist that substantially lower the perceived and actual cost of engagement in non-local search to a level that they are actually equivalent to local search, and can be engaged in permanently (also see Afuah & Tucci 2012). Thus, some open innovation practices, similar to information and communication technology (Zammuto et al. 2007), may be regarded as a toolkit using which the organization may in fact be casting *a wider net of local*

*search*. We would call for future research to identify which practices satisfy this criterion to derive further insights for the BTF. At the same time, we acknowledge that our findings may be conditional on our sample mainly consisting of small and innovative firms, which may search differently from larger, less innovative ones (Audia & Greve 2006). In this vein, we submit our insights as suggestion for future work to elaborate on reasons why ‘standard’ v- or u-shape between aspiration-performance and external search may turn or flex. Such future work may also further inquire the surprisingly different results we found when looking at the moderation effects of human capital and R&D, respectively. Given how we find significant effects for our joint-aspiration-performance measure only for human capital, no effects when only looking at historic aspirations, and our predicted effects for both measures for social aspirations suggests that these measures somehow interplay differently, an issue that may warrant future work, particularly of qualitative nature.

Our third contribution lies in our novel, practice-based appreciation of open innovation. Adhering to Chesbrough’s definitions, we think the best way to conceptualize *and* operationalize open innovation is as a set of practices. From a methodological perspective, this approach also tremendously reduces measurement error, given that no two companies—and possibly even no two researchers—may agree on a precise a priori definition required for good measurement (e.g., Podsakoff et al. 2003). Extending earlier work resting on predefined large-scale questionnaires (e.g., Laursen & Salter 2006; Leiponen & Helfat 2010), the inventory we present may be considered a useful initial attempt at more exhaustively capturing different forms of open innovation in which firms may engage, as well as a potential categorization of these into subdimensions. A logical extension of our reasoning would be a configuration-theory perspective on open innovation; indeed, recent work has begun linking open innovation to questions of

complementarities and fit (Saebi & Foss 2015).

### **Limitations and Suggestions for Future Research**

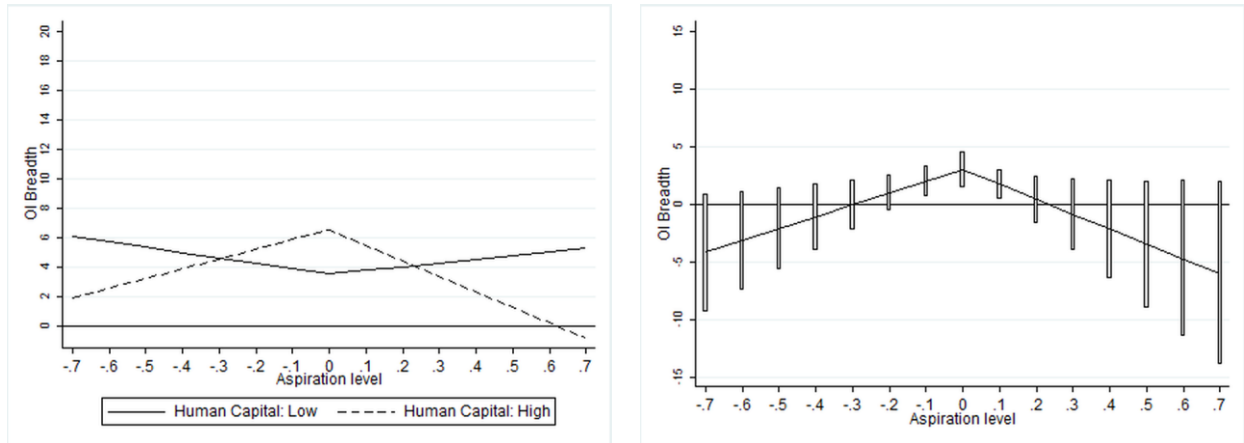
Like any study, ours is also subject to various limitations. First, our study concerns only UK-based firms, and therefore it may be of limited generalizability to other national contexts. In addition, by linking our survey data to financial data, we are working with a restricted sample, and therefore our results are not fully representative of the wide universe of small and medium sized firms in the UK. Second, beyond sample selection issues already discussed, another concern is survivor bias. While it is clear that, given the lagged structure of our variables, we lose younger firms, we have to admit that the logical opposite also holds true: we cannot observe firms that existed in the initial years for which we construct our independent variables, but which went out of business before the survey took place. Analyses we conduct, such as extending our sample by shortening the time window used to calculate HAP, indicate that this should not be of major concern. However, noting the differences between our sample, all respondents to the UK~IRC survey, it seems that our firms are slightly better performers. Yet, the difference between the worst performing firms and those we cannot observe because of survivor bias should be very small—similar to the logic underlying tests of non-response bias (Armstrong & Overton 1977). Also, given there is no indication that survivor bias and open innovation should be strongly and directly linked, we believe that survivor bias should not be a major concern with respect to the validity of our results. However, since we cannot observe the open innovation activities of non-surviving firms, we are unable to rule out this issue completely. Third, given we are relying on survey data, we have limited insight into actual managerial cognitions. While earlier qualitative and quantitative work lends some credibility to our reasoning, we would call for future work to study in-depth the search processes and practices that jointly comprise open

innovation, following earlier examples (e.g., Lopez-Vega et al. 2016; van Burg et al. 2014). Such work may also try to help validate the rationales we postulated to underlie the different moderation effects we hypothesized. Fourth, we need to acknowledge that, given the essentially cross-sectional nature of our data, we cannot rule out that actual mediation effects may be discovered when using inter-temporal data. This is particularly a concern due to the strong conceptual and empirical affinity between our three moderating variables. Further efforts to disentangle the pathways through which different parts of the firm's resource base shape its open innovation practices would be highly beneficial. Finally, our aspiration-level constructs may suffer from the shortcomings pointed out by Bromiley and Harris (2014).

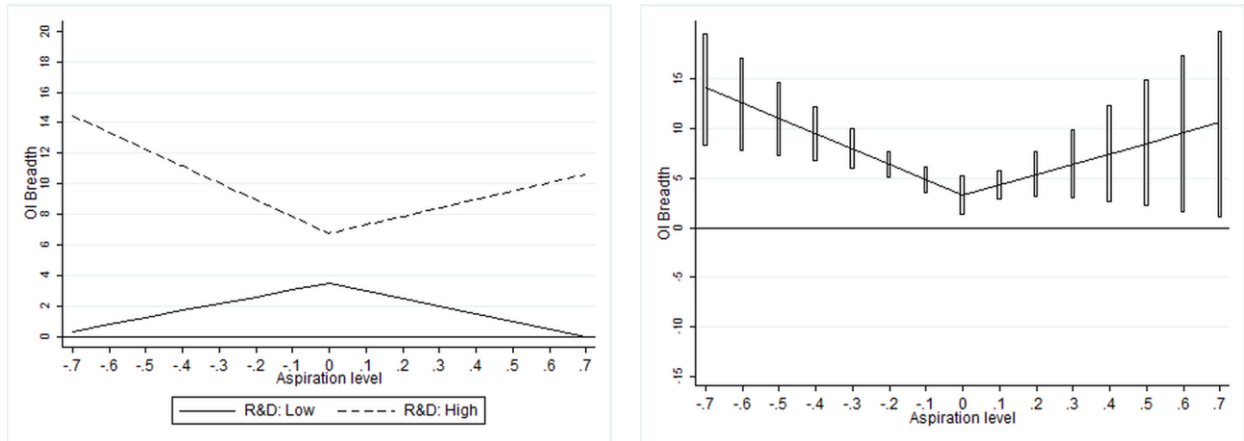
Limitations aside, we think this study is an important step in theorizing the emergence of open innovation. Extending the possibilities for future research pointed out above, we would call for our work to be extended to other contexts—for example, it is quite plausible that national or firm culture should influence collaborative behavior, and thus open innovation and search.

## TABLES AND FIGURES

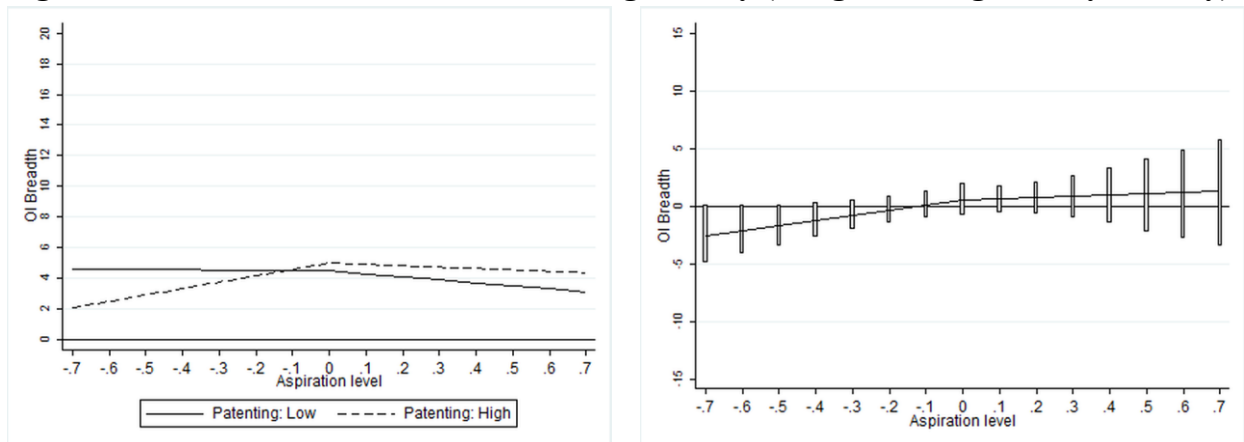
**Figure 1: Simulation of the Effect of Human Capital**



**Figure 2: Simulation of the Effect of R&D Investment**



**Figure 3: Simulation of the Effect of Patenting Activity (using Patenting Activity Dummy)**



Note: the images on the left show simulated marginal effects conditional on the aspiration level value, the line in the images on the right the difference in significance between the two simulated lines. The bar along the lines on the right depicts the confidence interval (at  $\alpha=0.1$ , two-tailed) of that difference; if it includes the zero, the difference is statistically insignificant.



**Table 1: Descriptive statistics (N=313)**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	OI Breadth	OI Breadth Index	Size	Age	Absorbed slack	Human Capital	R&D expenditure	Patenting (dummy)	Inverse Mills Ratio	Below Aspiration	Above Aspiration
(2)	0.971										
(3)	0.207	0.180									
(4)	0.022	0.007	0.352								
(5)	0.036	0.057	-0.166	-0.156							
(6)	0.135	0.156	-0.339	-0.225	0.095						
(7)	0.431	0.417	0.393	0.121	0.087	0.138					
(8)	0.062	0.103	-0.031	-0.041	0.036	0.118	0.087				
(9)	-0.227	-0.218	-0.836	-0.101	0.041	0.210	-0.430	-0.038			
(10)	0.028	0.028	0.170	0.070	-0.045	-0.241	0.067	0.027	-0.201		
(11)	-0.004	0.020	-0.008	-0.069	0.094	-0.044	0.107	0.124	-0.075	0.355	
Mean	4.37	8.02	3.82	2.80	0.00	0.00	-0.00	0.15	0.36	-0.08	0.06
S.D.	3.90	7.70	1.42	0.77	2.61	33.77	3.10		0.11	0.12	0.10
Median	4	6.18	4.09	2.83	-0.38	-12.4	-0.89	0	0.34	-0.02	0
Min	0.00	0.00	0.00	0.00	-1.14	-32.44	-3.29	0.00	0.16	-1.04	0.00
Max	15.00	38.46	6.84	4.73	37.19	67.56	7.53	1.00	0.85	0.00	0.70

Note: “OI Breadth Index” is a variation of the dependent variable used in robustness checks.

All correlations  $\geq |0.094|$  are significant at the 10% level,  $\geq |0.108|$  at the 5% level, and  $\geq |0.157|$  at the 1% level (two-tailed).

**Table 2: Results of Zero-Inflated Negative Binomial Regressions (N=313)**

	Model (1) Baseline	Model (2) Main Effect	Model (3) Interaction HC	Model (4) Interaction R&D	Model (5) Interaction Patents	Model (6) Full Model
Size	0.014 (0.050)	0.008 (0.053)	0.007 (0.049)	-0.001 (0.054)	0.008 (0.053)	-0.004 (0.049)
Age	-0.028 (0.071)	-0.030 (0.072)	-0.033 (0.070)	-0.028 (0.069)	-0.030 (0.072)	-0.033 (0.068)
Absorbed slack	0.000 (0.021)	0.002 (0.022)	0.002 (0.022)	0.000 (0.020)	0.007 (0.023)	0.002 (0.019)
Human Capital (HC)	<b>0.003†</b> (0.002)	<b>0.003†</b> (0.002)	<b>0.006**</b> (0.002)	<b>0.003†</b> (0.002)	<b>0.003*</b> (0.002)	<b>0.007**</b> (0.002)
R&D investment	<b>0.112**</b> (0.019)	<b>0.114**</b> (0.019)	<b>0.116**</b> (0.019)	<b>0.082**</b> (0.022)	<b>0.114**</b> (0.019)	<b>0.069**</b> (0.024)
Patenting (dummy)	0.084 (0.129)	0.095 (0.113)	0.134 (0.123)	0.080 (0.108)	0.166 (0.185)	0.146 (0.176)
Underperformance (UP)		<b>0.483†</b> (0.323)	-0.092 (0.448)	<b>1.021*</b> (0.440)	0.208 (0.328)	0.382 (0.485)
Overperformance (OP)		-0.556 (0.652)	-0.229 (0.663)	<b>-0.879†</b> (0.643)	-0.581 (0.852)	-0.820 (0.764)
UP * HC			<b>0.020*</b> (0.009)			<b>0.024*</b> (0.011)
OP * HC			<b>-0.029*</b> (0.014)			<b>-0.037*</b> (0.016)
UP * R&D				<b>-0.297*</b> (0.140)		<b>-0.420**</b> (0.133)
OP * R&D				<b>0.205†</b> (0.135)		<b>0.346*</b> (0.178)
UP * Patenting					<b>1.259*</b> (0.598)	<b>0.894†</b> (0.582)
OP * Patenting					0.087 (1.235)	0.383 (1.147)
Constant	<b>1.541**</b> (0.228)	<b>1.655**</b> (0.234)	<b>1.704**</b> (0.262)	<b>1.799**</b> (0.285)	<b>1.743**</b> (0.256)	<b>1.810**</b> (0.252)
Sector dummies	<b>Yes**</b>	<b>Yes**</b>	<b>Yes**</b>	<b>Yes**</b>	<b>Yes**</b>	<b>Yes**</b>
Chi <sup>2</sup> Value	78.34**	91.89**	137.6**	104.0**	96.48**	326.2**
Log-pseudolikelihood	-765.6	-764.7	-762.0	-762.9	-763.8	-758.1

Notes: Robust standard errors for one-tailed tests clustered by 2-digit SIC code (in parentheses). Sector-level dummies included. † significant at 10%; \* significant at 5%; \*\* significant at 1%

Variables used for inflation were firm size, age, perceived competitive pressure (number of competitors—here, we experimented with both the number from the UK Office of National Statistics, as well as the perceived number of competitors reported in the survey), sales revenue growth objective (survey), and an industry-level measure of formal IP protection (see Cassiman & Veugelers 2006).

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## APPENDIX

### List of Open Innovation Practices Used in the Survey

Practice	Assigned Factor*	Factor loadings		
		(1) “classic” R&D partnerships	(2) non-R&D partnership	(3) “open” R&D partnerships
Engaging directly with lead users and early adopters	3	0.3162	0.1979	0.4557
Participating in open source software development	3	0.0086	0.1856	0.6328
Exchanging ideas through submission websites and idea “jams”, idea competitions	3	0.0486	0.0270	0.7987
Participating in or setting up innovation networks/hubs with other firms	3	0.2511	0.1872	0.6844
Sharing facilities with other organizations, inventors, researchers etc.	3	0.3602	0.2642	0.5070
Joint R&D	(1)	0.6539	0.4108	0.0336
Joint purchasing of materials or inputs	2	0.1398	0.8035	0.0721
Joint production of goods or services	2	0.1189	0.8350	0.0862
Joint marketing/co-branding	2	0.1192	0.6990	0.2173
Participating in research consortia	1	0.7454	0.1813	0.1642
Joint university research	1	0.7709	0.0617	0.0690
Licensing in externally developed technologies	1	0.5269	0.1187	0.2839
Outsourcing or contracting out R&D projects	1	0.6067	0.0968	0.1100
Providing contract research to others	1	0.6603	0.0881	0.1485
Joint ventures, acquisitions and incubations	---	0.4288	0.4020	0.2356

\* only assigned to a factor if loading > 0.4 on focal factor and < 0.4 on all others. “Joint R&D” has minor cross-loadings, but a clear primary loading (>0.6)—we ran regression both including and ignoring this variable in the respective factor.

\*\* Factor loadings as taken from exploratory factor analysis with principle component method and Kaiser criterion.

## ENDNOTES

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- <sup>1</sup> Recent reviews (e.g., Bromiley & Harris 2014) and the emerging literature on behavioral strategy (e.g., Powell et al. 2011) go in more depth about the rationale for these shifts in managerial decision-making patterns, which, amongst other things, may for example relate to changing risk-taking propensities or envy.
  - <sup>2</sup> For waves 1-3, the original 12-pages long questionnaire was sent out; however, in order to increase the response rate, shorter versions were sent for the following waves.
  - <sup>3</sup> Except for conventional business services, where respondents have been found to have a significantly smaller turnover than the non-respondents. In addition, in additional analysis we conducted, it seems that UK~IRC firms are, on average more patenting intensive in all sectors. In addition, they have higher R&D expenditure, an effect largely driven by knowledge-intensive business services. Static comparisons against the mean values of human capital from the UK Innovation Survey also suggest that UK~IRC firms may have higher human capital.
  - <sup>4</sup> This is in part due the fact that these are small, often privately owned firms that are only required to submit abbreviated accounts to the government registry.
  - <sup>5</sup> We are indebted to our careful reviewers who pointed out this shortcoming to us.
  - <sup>6</sup> While this value is beyond the range of 0.1 to 0.3 commonly identified in studies on aspiration levels, our results remain unchanged when using those weights. As we will note later, this finding may however be attributed to the fact that our results are largely driven by SAP and not by HAP.
  - <sup>7</sup> However, the p-value of the Vuong test comparing our ZINB estimation with a negative binomial model is exactly 5%, and beyond 5% for some of the different regression models we estimate, for example Models 4 and 5.
  - <sup>8</sup> Given that we cannot simulate zero-inflated negative binomial regressions using this method, the figures are drawn from simple OLS regressions. Alternatively, we also employed standard negative binomial regression, OLS regressions using a logged version of the dependent variable, as well as the approach suggested by Brambor and co-authors (2006). All results are fully consistent with the figures shown herein.